Performance metrics

Dmytro Fishman (dmytro.fishman@ut.ee)
# Deadlines

<table>
<thead>
<tr>
<th>Assignment</th>
<th>Date of assignment</th>
<th>Deadline (midnight 23:59)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW1</td>
<td>Sep 7</td>
<td>Sep 20</td>
</tr>
<tr>
<td>HW2</td>
<td>Sep 21</td>
<td>Oct 4</td>
</tr>
<tr>
<td>HW3</td>
<td>Oct 5</td>
<td>Oct 18</td>
</tr>
<tr>
<td>Paper summary</td>
<td>Oct 12</td>
<td>Oct 26</td>
</tr>
<tr>
<td>HW4</td>
<td>Oct 19</td>
<td>Nov 1</td>
</tr>
<tr>
<td>HW5</td>
<td>Nov 2</td>
<td>Nov 15</td>
</tr>
<tr>
<td>HW6</td>
<td>Nov 23</td>
<td>Dec 6</td>
</tr>
<tr>
<td>Project</td>
<td>Oct 5 - 7</td>
<td>Dec 14 - 16</td>
</tr>
</tbody>
</table>

Make sure to **double check** the **deadlines** for all assignments
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

Random Forest

Boosting (AdaBoost and GBM)

Stacking and Blending
Multiple models are built on training data

Linear Regression
Ridge Regression
Lasso Regression

\[ y = 1.6 + 0.79x + 3.28 + 0.14x + 1.94 + 0.64x + 0.14x \]

Average the predictions

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>3.18</td>
<td>5.55</td>
</tr>
<tr>
<td>Ridge</td>
<td>3.23</td>
<td>5.17</td>
</tr>
<tr>
<td>Lasso</td>
<td>3.57</td>
<td>4</td>
</tr>
</tbody>
</table>

Average: 3.32
Multiple models are built on training data.

Training data

<table>
<thead>
<tr>
<th>Test</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>Dog</td>
</tr>
<tr>
<td>Model 2</td>
<td>Dog</td>
</tr>
<tr>
<td>Model 3</td>
<td>Cat</td>
</tr>
<tr>
<td>Ensemble</td>
<td></td>
</tr>
<tr>
<td>TRUE</td>
<td>Dog</td>
</tr>
</tbody>
</table>

Majority voting
Multiple models are built on training data.
Multiple models are built on training data.

- Model 1 predicts Dog.
- Model 2 predicts Dog.
- Model 3 predicts Cat.

The Ensemble predicts Dog.

The Test data predicts Dog.

**Majority voting**

Dog wins!
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

The Random Forest algorithm

Random Forest

Boosting (AdaBoost and GBM)

Stacking and Blending
We can estimate the weight of each model based on CV on training data.

Training data

<table>
<thead>
<tr>
<th>Model</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>0.33</td>
</tr>
<tr>
<td>M2</td>
<td>0.37</td>
</tr>
<tr>
<td>M3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Relative weight

Previously each model was given only one vote.

Now each model has different number of votes.

<table>
<thead>
<tr>
<th>Model</th>
<th>Votes for Dog</th>
<th>Votes for Cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>33</td>
<td>70</td>
</tr>
<tr>
<td>M2</td>
<td>37</td>
<td>30</td>
</tr>
<tr>
<td>M3</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Ensemble parlement

- Dog: 100 sits
  - M1: 33 votes
  - M2: 37 votes
- Cat: 70 votes
  - M3: 30 votes

2 for Dog
1 for Cat
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

The Random Forest algorithm

Random Forest

Boosting (AdaBoost and GBM)

Stacking and Blending
Bootstrapping + Aggregation = Bagging

Aggregating predictions produced by models trained on random bootstraps of data
Bootstrapping + Aggregation = Bagging

Aggregating predictions produced by models trained on random bootstraps of data
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

The Random Forest algorithm

Random Forest

Boosting
(AdaBoost and GBM)

Stacking and Blending
We add **a new step** into the tree building algorithm:

0. Choose a **random set** of features

1. Evaluate **all possible splits**

2. Choose the **best split**

Bag #1

- **Heads** means we keep $X_2$
- **Tail** means we keep $X_1$
We can build an ensemble.
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”
We modified importance scores

Modified importance scores again

Both methods train ensembles **sequentially** (one model after another)
Both methods train ensembles **sequentially** (one model after another)

**AdaBoost**

**Gradient Boosting**
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

Random Forest

Boosting (AdaBoost and GBM)

Stacking and Blending
Stacking or blending

Separate ML model

Final predictions
Basic ensembling

Weighted ensembling

Bagging ensembling

“In previous episodes…”

Random Forest

Boosting (AdaBoost and GBM)

Stacking and Blending
Supervised Learning

Classification

Regression

Unsupervised Learning

Clustering

Machine Learning

Dimensionality reduction

Unsupervised Learning

Clustering

Reinforcement Learning
Classification

Regression
Classification

Regression

Classification

Regression
Everything is easy, here we calculate the **proportion** of correctly guessed instances.
Everything is easy, here we calculate the proportion of correctly guessed instances.

Accuracy = \( \frac{4}{5} \)
Everything is easy, here we calculate the proportion of correctly guessed instances.

Accuracy = $\frac{4}{5}$
The good thing about **accuracy** is that it is easily interpretable.

\[
\text{Accuracy} = 80\%
\]

\[
\text{Correctly guessed instances} \quad \text{The number of all instances}
\]

The diagram shows a scatter plot with two axes, \(X_1\) and \(X_2\), and points marked in blue and red.
The good thing about **accuracy** is that it is easily interpretable.

Accuracy = **80%**

![Diagram showing classification results with accuracy 80%](image-url)
The good thing about **accuracy** is that it is easily interpretable.

Accuracy = 80%

Classifier $X$

Random Generator
The good thing about **accuracy** is that it is easily interpretable.

Accuracy = **80%**

Accuracy ~ **50%**
The good thing about **accuracy** is that it is easily interpretable.

**Accuracy = 80%**

You can easily estimate the **added value** of your classifier over a query to [https://www.random.org/](https://www.random.org/)

**Accuracy ~50%**
It is not always informative to use **random generator** as a baseline.

Accuracy = \textbf{80\%}

Random Generator

Accuracy $\sim \textbf{50\%}$
What if we have slightly different situation?
What if we have slightly different situation?

Only one instance of \textbf{opposite} class
What if we have slightly different situation?

Classifier the predicts all instances as blue

Only one instance of opposite class
What if we have slightly different situation?

Only one instance of **opposite** class

Classifier the predicts all instances as **blue**

**Majority** class
(most frequent class)
What if we have slightly different situation?

Classifier the predicts all instances as blue

Only one instance of opposite class

Accuracy = ?%
What if we have slightly different situation?

Only one instance of opposite class

Classifier the predicts all instances as blue

Accuracy = 80\%
What if we have slightly different situation?

Accuracy = ?%
What if we have slightly different situation?

Accuracy = 9/10
What if we have slightly different situation?

Accuracy = 90%
What if we have slightly different situation?

Accuracy = 90%

What is the **accuracy** of the random generator in this case?

~?%
What if we have slightly different situation?

Accuracy = 90%

What is the accuracy of the random generator in this case?

~50%
Sometimes being better than random guess **is not** enough!

Accuracy = 90%

What is the **accuracy** of the random generator in this case?

$\sim 50\%$
Segmentation problem - predicting class for each pixel in the image (in this case pedestrian and background)
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Person < 10% pixels
Segmentation problem - predicting class for each pixel in the image (in this case pedestrian and background)

Background > 90% pixels

Person < 10% pixels
Segmentation problem - predicting **class** for each pixel in the image (in this case **pedestrian** and **background**)

Background > 90% pixels

**Majority** class prediction is +90% accurate
Segmentation problem - predicting class for each pixel in the image (in this case pedestrian and background)

Background > 90% pixels

Majority class prediction is +90% accurate

Random guess is only 50% accurate
Sometimes being simply better than random guess is not enough!
Ok, so what can we do? (if not accuracy then who?)
Ok, so what can we do? (if not accuracy then who?)
Ok, so what can we do? (if not accuracy then who?)
Ok, so what can we do? (if not **accuracy** then who?)
Ok, so what can we do? (if not accuracy then who?)
Ok, so what can we do? (if not accuracy then who?)
Ok, so what can we do? (if not **accuracy** then who?)
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Ok, so what can we do? (if not **accuracy** then who?)
One of the classes is called “positive” and the other “negative”. This division is arbitrary.
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “positive” and the other “negative”. This division is arbitrary.

Let’s call the red class “negative”.

Predicted

Actual
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “positive” and the other “negative”. This division is arbitrary.

Let’s call the red class “negative”.

And the blue class will call “positive”.
Ok, so what can we do? (if not \textit{accuracy} then who?)

One of the classes is called \textbf{“positive”} and the other \textbf{“negative”}. This division is arbitrary.
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called "positive" and the other "negative". This division is arbitrary.

True Positive - positive class predicted as positive
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “positive” and the other “negative”. This division is arbitrary.
Ok, so what can we do? (if not **accuracy** then who?)

One of the classes is called “**positive**” and the other “**negative**”. This division is arbitrary.

**False Negative** - positive class predicted as negative
One of the classes is called “positive” and the other “negative”. This division is arbitrary.

Predicted

Actual

False Positive - negative class predicted as positive
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “positive” and the other “negative”. This division is arbitrary.
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “positive” and the other “negative”. This division is arbitrary.
Ok, so what can we do? (if not accuracy then who?)

One of the classes is called “**positive**” and the other “**negative**”. This division is arbitrary.
Type I Error

You’re pregnant!

Type II Error

You’re not pregnant!
*provided that pregnant is a positive class
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.
**Confusion matrix** is a powerful tool to analyse the performance of machine learning algorithms.
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.

Problematic classifiers usually manifest themselves in empty columns.
What about this example?
What about this example?
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms. Problematic classifiers usually manifest themselves in empty columns.
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithm.
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.

How to interpret this number?
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.
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Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.
These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix

Number of correctly predicted as positive

Recall = \( \frac{TP}{TP + FN} \)

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

Number of correctly predicted as positive

Recall = TP / (TP + FN)

The total number of actual positive

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

Number of correctly predicted as positive

The total number of actual positive

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>○</td>
<td>TN</td>
</tr>
<tr>
<td>□</td>
<td>FN</td>
</tr>
</tbody>
</table>

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?

Number of correctly predicted as positive

Recall = $\frac{TP}{TP + FN}$

The total number of actual positive

Precision = $\frac{TP}{TP + FP}$
**Recall** and **Precision** can help summarise the confusion matrix.

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>●</td>
<td>TN</td>
</tr>
<tr>
<td>●</td>
<td>FN</td>
</tr>
<tr>
<td>□</td>
<td>FP</td>
</tr>
<tr>
<td>□</td>
<td>TP</td>
</tr>
</tbody>
</table>

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)
Recall and Precision can help summarise the confusion matrix.

Recall = \[ \frac{TP}{TP + FN} \]

Precision = \[ \frac{TP}{TP + FP} \]

Number of correctly predicted as positive

The total number of positive

The total number of points predicted as positive

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

These are four numbers (TN, TP, FN and FP), can we have fewer indicators?
Recall and Precision can help summarise the confusion matrix.

\[ \text{Recall} = \frac{TP}{TP + FN} \]

Recall = TP / (TP + FN)

The total number of actual as positive

The total number of points predicted as positive

\[ \text{Precision} = \frac{TP}{TP + FP} \]

Precision = TP / (TP + FP)

Number of correctly predicted as positive

Number of correctly predicted as positive

Predicted

Actual

\[ \begin{array}{c|cc}
\text{TN} & \text{FP} \\
\hline
0 & 1 \\
\text{FN} & \text{TP} \\
0 & 9 \\
\hline
\sum & 0 & 10 \\
\end{array} \]
**Recall** and **Precision** can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>0</strong></td>
</tr>
<tr>
<td><strong>0</strong></td>
<td><strong>0</strong></td>
</tr>
<tr>
<td><strong>1</strong></td>
<td><strong>1</strong></td>
</tr>
</tbody>
</table>

The total number of points predicted as positive: \( \sum = 10 \)

The total number of actual positive: \( \sum = 9 \)

Number of correctly predicted as positive

Number of correctly predicted as positive
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

The total number of actual positive

The total number of points predicted as positive
**Recall** and **Precision** can help summarise the confusion matrix.

Recall = \[ \frac{TP}{TP + FN} \]

Precision = \[ \frac{TP}{TP + FP} \]

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>0</strong></td>
<td><strong>0</strong></td>
</tr>
<tr>
<td><strong>1</strong></td>
<td><strong>9</strong></td>
</tr>
<tr>
<td><strong>9</strong></td>
<td><strong>1</strong></td>
</tr>
</tbody>
</table>

The total number of points predicted as positive: \( \sum \) 10

The total number of actual as positive: \( \sum \) 10

Number of correctly predicted as positive:

\[
\text{Recall} = \frac{TP}{TP + FN} \\
\text{Precision} = \frac{TP}{TP + FP}
\]
Recall and Precision can help summarise the confusion matrix.

Recall = \frac{9}{TP + FN}

Precision = \frac{TP}{TP + FP}

The total number of points predicted as positive.

The total number of actual as positive.

Number of correctly predicted as positive.

Number of correctly predicted as positive.
**Recall** and **Precision** can help summarise the confusion matrix.

- **Recall**:
  \[ \text{Recall} = \frac{9}{TP + FN} \]
  Number of correctly predicted as **positive**

- **Precision**:
  \[ \text{Precision} = \frac{TP}{TP + FP} \]
  Number of correctly predicted as **positive**

The total number of actual positive points is 9.

The total number of points predicted as positive is 10.

Confusion Matrix:

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>9</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ \sum \]

\[ \sum \]
Recall and Precision can help summarise the confusion matrix.

Recall = \frac{9}{(TP + FN)}

The total number of actual positive

Precision = \frac{TP}{(TP + FP)}

The total number of points predicted as positive

Actual

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>TP</td>
<td></td>
<td>10</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{9}{(TP + FN)} \)

The total number of actual positive

Number of correctly predicted as positive

Precision = \( \frac{TP}{(TP + FP)} \)

The total number of points predicted as positive

The total number of points predicted as positive

\[
\begin{array}{c|cc}
\text{Actual} & \text{FN} & \text{TP} \\
\hline
\text{FP} & 0 & 1 \\
\text{TP} & 9 & 0 \\
\text{TN} & 0 & 10 \\
\end{array}
\]
Recall and Precision can help summarise the confusion matrix.

Recall = \[ \frac{9}{9 + 0} \]

The total number of actual positive

Precision = \[ \frac{TP}{TP + FP} \]

Number of correctly predicted as positive

The total number of points predicted as positive
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{9}{(9)} \)

The total number of actual positive

Precision = \( \frac{TP}{(TP + FP)} \)

The total number of points predicted as positive

\[
\begin{array}{c|cc}
\text{Predicted} & \text{FN} & \text{TP} \\
\hline
\text{Actual} & 0 & 9 \\
\sum & 0 & 10 \\
\end{array}
\]
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{9}{9} \)

Precision = \( \frac{\text{TP}}{\text{TP + FP}} \)

Number of correctly predicted as positive

The total number of points predicted as positive

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>9</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
</tr>
</tbody>
</table>
Recall and Precision can help summarise the confusion matrix.

**Recall** = \( \frac{TP}{TP + FN} \)

**Precision** = \( \frac{TP}{TP + FP} \)

The total number of points predicted as positive:

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
</tr>
</tbody>
</table>

Number of correctly predicted as positive:

- True Positive (TP): 9
- False Positive (FP): 1
- False Negative (FN): 0
- True Negative (TN): 0

The total number of points predicted as positive: 10
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \( \frac{TP}{TP + FP} \)

The total number of points predicted as positive.
**Recall** and **Precision** can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual **positive** cases.

Precision = \( \frac{TP}{TP + FP} \)

The **total number** of points predicted as **positive**.
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \( \frac{TP}{TP + FP} \)

The total number of points predicted as positive.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

\[ \sum 0 \quad 10 \]
\[ \sum 1 \quad 9 \]
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Number of correctly predicted as positive

Precision = \( \frac{TP}{TP + FP} \)

The total number of points predicted as positive

\[
\begin{array}{ccc}
\text{Actual} & \text{Predicted} & \sum \\
\text{TN} & 0 & 1 \\
\text{FP} & 1 & 0 \\
\text{FN} & 0 & 9 \\
\sum & 0 & 10
\end{array}
\]
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0
We correctly predicted 100% of actual positive cases.

Number of correctly predicted as positive

Precision = \( \frac{9}{(TP + FP)} \)

The total number of points predicted as positive

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

\( \sum \)
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \( \frac{9}{(TP + FP)} \)

The total number of points predicted as positive.
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \(\frac{9}{(TP + FP)}\)

The total number of points predicted as positive.

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

The total number of points predicted as positive is 10.
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \( \frac{9}{10} \)

The total number of points predicted as positive.
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = \frac{9}{10}

The total number of points predicted as positive is 10.
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0

We correctly predicted 100% of actual positive cases.

Precision = 0.9

```
<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FP</td>
</tr>
<tr>
<td>TN</td>
<td></td>
</tr>
<tr>
<td>FN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TP</td>
</tr>
</tbody>
</table>
```

```
<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td></td>
</tr>
<tr>
<td>FN</td>
<td></td>
</tr>
<tr>
<td>FP</td>
<td></td>
</tr>
<tr>
<td>TN</td>
<td></td>
</tr>
</tbody>
</table>
```

\[ \sum \]
Recall and Precision can help summarise the confusion matrix

Recall = 1.0
We correctly predicted 100% of actual positive cases

90% of all predicted positive were actually positive

Precision = 0.9

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TP</td>
<td>9</td>
</tr>
</tbody>
</table>

\[ \sum = 0 + 1 + 0 + 9 = 10 \]
Recall and Precision can help summarise the confusion matrix

Recall = \textbf{1.0}

We correctly predicted \textbf{100\%} of actual \textbf{positive} cases

Precision = \textbf{0.9}

90\% of all predicted \textbf{positive} were actually \textbf{positive}
**Recall** and **Precision** can help summarise the confusion matrix.

Recall = **1.0**

Both **Recall** and **Precision** are high, does it automatically mean that our classifier is good?

Precision = **0.9**
Recall and Precision can help summarise the confusion matrix.

Recall = 1.0
Precision = 0.9
Recall and Precision can help summarise the confusion matrix.

This classifier completely ignores the second class.

We got high Recall and Precision just because we defined blue class as positive.
Ok, so what can we do? (if not accuracy then who?)

Let's call the red class "negative"

And the blue class will call "positive"

How Recall and Precision are going to change if we flip the positive/negative assignment?
Ok, so what can we do? (if not accuracy then who?)

How Recall and Precision are going to change if we flip the positive/negative assignment?

Let’s call the blue class “negative”

And the red class will call “positive”
How **Confusion Matrix** is going to change if we flip the positive/negative assignment?
How **Confusion Matrix** is going to change if we flip the positive/negative assignment?
How **Confusion Matrix** is going to change if we flip the positive/negative assignment?
How **Confusion Matrix** is going to change if we flip the positive/negative assignment?

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TN</td>
</tr>
<tr>
<td>Actual</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Sum: 9

Sum: 10 0
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

- Number of correctly predicted as positive
- The total number of actual positive

Precision = \( \frac{TP}{TP + FP} \)

- Number of correctly predicted as positive
- The total number of points predicted as positive

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ \sum \]

\[ \sum \]

\[ \sum \]
Recall and Precision can help summarise the confusion matrix.

Recall = \frac{0}{(TP + FN)}

Number of correctly predicted as positive

The total number of actual positive

Precision = \frac{0}{(TP + FP)}

Number of correctly predicted as positive

The total number of points predicted as positive
Recall and Precision can help summarise the confusion matrix.

Number of correctly predicted as positive

Recall = \( \frac{0}{0 + FN} \)

The total number of actual positive

Precision = \( \frac{0}{0 + FP} \)

The total number of points predicted as positive

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>1</td>
</tr>
<tr>
<td>TP</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>9</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ \sum = 10 \quad 0 \]

\[ \sum = 9 \quad 1 \]
Recall and Precision can help summarise the confusion matrix.

Number of correctly predicted as positive

Recall = \( \frac{0}{0 + 1} \)

The total number of actual positive

Precision = \( \frac{0}{0 + 0} \)

The total number of points predicted as positive

<table>
<thead>
<tr>
<th>Predicted</th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>TN</td>
<td>FP</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

\( \sum \)

\( \sum \)
Recall and Precision can help summarise the confusion matrix.

Recall = 0.0

Precision = NaN
Recall and Precision can help summarise the confusion matrix:

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Recall = 0.0

We correctly predicted 0% of actual positive cases.

NaN% of all predicted positive were actually positive.

Precision = NaN
Recall and Precision for class red

Recall = 0.0

We correctly predicted 0% of actual positive cases

NaN% of all predicted positive were actually positive

Precision = NaN
Recall and Precision for class red

Recall = 0.0

We correctly predicted 0% of actual positive cases

NaN% of all predicted positive were actually positive

Precision = NaN

Recall and Precision for class blue

Recall = 1.0

We correctly predicted 100% of actual positive cases

90% of all predicted positive were actually positive

Precision = 0.9
Recall and Precision for class red

Recall = 0.0
Precision = NaN

We correctly predicted 0% of actual positive cases

NaN% of all predicted positive were actually positive

Recall and Precision for class blue

Recall = 1.0
Precision = 0.9

We correctly predicted 100% of actual positive cases

90% of all predicted positive were actually positive

Calculate recall and precision for each class to get a more complete picture of classifier’s performance
Recall and Precision for class red

Recall = 0.0
Precision = NaN

We correctly predicted 0% of actual positive cases

NaN% of all predicted positive were actually positive

Recall and Precision for class blue

Recall = 1.0
Precision = 0.9

We correctly predicted 100% of actual positive cases

90% of all predicted positive were actually positive

Calculate recall and precision for each class to get a more complete picture of classifier’s performance

*Is it possible to combine recall and precision in one value?
for class red

Recall = 0.0

Precision = NaN

for class blue

Recall = 1.0

Precision = 0.9
for class red

Recall = 0.0

Precision = NaN

for class blue

Recall = 1.0

Precision = 0.9

F1-score

\[
F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}
\]
for class red

Recall = 0.0
Precision = NaN
F1-score = ?

for class blue

Recall = 1.0
Precision = 0.9
F1-score = ?

\[
F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}
\]
for class red

Recall = 0.0
Precision = NaN
F1-score = NaN

for class blue

Recall = 1.0
Precision = 0.9
F1-score = ?

\[ F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]
for class red

Recall = 0.0
Precision = NaN
F1-score = NaN

for class blue

Recall = 1.0
Precision = 0.9
F1-score = ?

$$F1 = 2 \times \frac{Recall \times Precision}{Recall + Precision}$$
for class red

Recall = 0.0

Precision = NaN

F1-score = NaN

for class blue

Recall = 1.0

Precision = 0.9

F1-score = ?

\[ F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]
for class **red**

Recall = 0.0

Precision = **NaN**

F1-score = **NaN**

for class **blue**

Recall = **1.0**

Precision = **0.9**

F1-score = ?

\[
F1 = 2 \times \frac{1.0 \times 0.9}{1.0 + 0.9}
\]
for class **red**

- **Recall** = 0.0
- **Precision** = NaN
- **F1-score** = NaN

\[
F1 = 2 \times \frac{0.9}{1.9}
\]

for class **blue**

- **Recall** = 1.0
- **Precision** = 0.9
- **F1-score** = ?
for class **red**

Recall = 0.0

Precision = NaN

$F1 = \frac{1.8}{1.9}$

for class **blue**

Recall = 1.0

Precision = 0.9

$F1$-score = ?
for class red

Recall = 0.0
Precision = NaN
F1-score = NaN

\[ F1 = 0.947 \]

for class blue

Recall = 1.0
Precision = 0.9
F1-score = ?
for class **red**

Recall = 0.0

Precision = NaN

F1-score = NaN

---

**F1** = 0.947

for class **blue**

Recall = 1.0

Precision = 0.9

F1-score = 0.947
for class red

Recall = 0.0

Precision = NaN

F1-score = NaN

for class blue

Recall = 1.0

Precision = 0.9

F1-score = 0.947

\[ F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]
F1-score is a **harmonic mean** between recall and precision

\[
F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}
\]
F1-score is a **harmonic mean** between recall and precision

\[ F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]

F1-score is **also known** as ...
F1-score is a harmonic mean between recall and precision

\[ F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]

F1-score is also known as the Sørensen-Dice coefficient
F1-score is a **harmonic mean** between recall and precision

\[
F1 = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}
\]

F1-score is **also known** as the **Dice coefficient**
F1-score is a **harmonic mean** between recall and precision.

\[ F1 = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]

F1-score is **also known** as the **Dice** coefficient.

\[ \text{Dice} = \frac{2 \times TP}{2 \times TP + FP + FN} \]
Is this even possible?

\[
2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}}
\]

F1-score

Dice coefficient
Is this even **possible**?

\[
2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

**Dice coefficient**
Is this even possible?

\[
\text{Recall} = \frac{TP}{TP + FN} \\
2 \ast \frac{\text{Recall} \ast \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \ast TP}{2 \ast TP + FP + FN}
\]
Is this even **possible**?

\[
2 \times \frac{TP}{TP + FN} \ast \text{Precision} + \text{Precision} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

\[
\text{Recall} = \frac{TP}{TP + FN}
\]
Is this even possible?

\[
2 \times \frac{TP}{TP + FN} \times \text{Precision} + \text{Precision} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
2 \times \frac{TP}{TP + FN} \times \text{Precision} + \text{Precision} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

\[
\text{Precision} = \frac{TP}{TP + FP}
\]
Is this even possible?

\[
\begin{align*}
2 \times & \frac{TP}{TP + FN} \times \frac{TP}{TP + FP} \\
= & \frac{2 \times TP}{2 \times TP + FP + FN} \\
\text{Precision} = & \frac{TP}{TP + FP}
\end{align*}
\]
Is this even possible?

\[ 2 \times \frac{TP}{TP + FN} \times \frac{TP}{TP + FP} = \frac{2 \times TP}{2 \times TP + FP + FN} \]

Dice coefficient
Is this even possible?

\[
\frac{TP}{TP + FN} \times \frac{TP}{TP + FP} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
2 \times \frac{TP \times TP}{(TP + FN) \times (TP + FP)} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
2 \times \frac{TP \times TP}{(TP + FN) \times (TP + FP)} + \frac{TP}{TP + FN} + \frac{TP}{TP + FP} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
2 \cdot \frac{TP \cdot TP}{(TP + FN) \cdot (TP + FP)} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
\frac{2 \times TP}{\frac{TP \times TP}{(TP + FN) \times (TP + FP)} + \frac{TP \times (TP + FN)}{(TP + FN) \times (TP + FP)}} = \frac{2 \times TP}{(2 \times TP + FP + FN)}
\]
Is this even possible?

\[
\frac{2 \times TP \times TP}{2 \times TP + FP + FN} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even \textbf{possible}?

\[
\frac{2 \cdot TP}{2 \cdot TP + FP + FN} = \frac{2 \cdot TP}{(TP + FN) \cdot (TP + FP)}
\]
Is this even possible?

\[
\frac{2 \ast TP}{TP \ast (TP + FP) + TP \ast (TP + FN)} = \frac{2 \ast TP}{2 \ast TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
\frac{2 \times TP \times TP}{TP \times (TP + FP) + TP \times (TP + FN)} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even **possible**?

\[
2 \times \frac{TP \times TP}{TP \times (TP + FP + TP + FN)} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

*Dice coefficient*
Is this even possible?

\[
\frac{2 \times TP \times TP}{TP \times (TP + FP + TP + FN)} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
\frac{2\times TP \times TP}{TP \times (TP + FP + TP + FN)} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
2 \* \frac{TP}{TP + FP + TP + FN} = \frac{2 \* TP}{2 \* TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
\frac{2 \times TP}{2 \times TP + FP + FN} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

Dice coefficient
Is this even possible?

\[
\frac{2 \times TP}{2 \times TP + FP + FN} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

F1-score  

Dice coefficient
Is this even possible?

\[
\frac{2 \times TP}{2 \times TP + FP + FN} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

F1-score \quad \Downarrow \quad \text{Dice coefficient}
for class **red**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Recall</strong></td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Precision</strong></td>
<td>NaN</td>
</tr>
<tr>
<td><strong>F1-score/Dice</strong></td>
<td>NaN</td>
</tr>
</tbody>
</table>

for class **blue**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Recall</strong></td>
<td>1.0</td>
</tr>
<tr>
<td><strong>Precision</strong></td>
<td>0.9</td>
</tr>
<tr>
<td><strong>F1-score/Dice</strong></td>
<td>0.947</td>
</tr>
</tbody>
</table>

\[
F1/Dice = 2 \cdot \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}
\]
for class red

Recall = 0.0

Precision = NaN

$F_1$-score/Dice = NaN

\[
F_1/Dice = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \times \text{TP}}{2 \times \text{TP} + \text{FP} + \text{FN}}
\]
for class **red**

Recall = 0.0

Precision = NaN

**F1-score/Dice** = 0.0

\[
F1/Dice = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]
for class red

Recall = 0.0

Precision = NaN

F1-score/Dice = 0.0

for class blue

Recall = 1.0

Precision = 0.9

F1-score/Dice = 0.947
So far…
The good thing about accuracy is that it is easily interpretable.

So far...

Accuracy = 80%
So far...

**Accuracy** does not help to detect lazy (majority class) classifier

Both are dummy and can be harmful
Confusion matrix is a powerful tool to analyse the performance of machine learning algorithms.

So far...

One of the classes is completely ignored.
Recall and Precision can help summarise the confusion matrix.

Recall = \( \frac{TP}{TP + FN} \)

Precision = \( \frac{TP}{TP + FP} \)

Number of correctly predicted as positive

The total number of actual positive

So far…
Values of **Recall** and **Precision** depend on the definition of the “positive” class

Recall = 0.0

We correctly predicted 0% of actual **positive** cases

**NaN**% of all predicted **positive** were actually **positive**

Precision = **NaN**

Recall = 1.0

We correctly predicted 100% of actual **positive** cases

90% of all predicted **positive** were actually **positive**

Precision = **0.9**

So far…
So far...

**F1-score** is a harmonic mean between recall and precision

\[
2 \ast \frac{\text{Recall} \ast \text{Precision}}{\text{Recall} + \text{Precision}} = \frac{2 \ast \text{TP}}{2 \ast \text{TP} + \text{FP} + \text{FN}}
\]

F1-score is also known as the **Dice coefficient**
Accuracy = 80%

Confusion matrix

Actual

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TN</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TP</td>
<td>3</td>
</tr>
</tbody>
</table>

Recall = 1.0

Precision = 0.75

F1-score/Dice = 6/7
Can we please have just **one** number?
Can we please have just **one** number?

A bit more balanced example
Let's assume that we have a classifier that assigned the following probabilities of a data point to be positive (i.e. blue).

Can we please have just one number?

A bit more balanced example

Let's assume that we have a classifier that assigned the following probabilities of a data point to be **positive** (i.e. **blue**).
Can we please have just one number?

Let's assume that we have a classifier that assigned the following probabilities of a data point to be positive (i.e. blue).
Can we please have just one number?

Let's assume that we have a classifier that assigned the following probabilities of a data point to be positive (i.e. blue)

Probability for the point to belong to positive class
Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**
Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**

Decision tree
Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**

What is the **probability** of this point to be **blue**?
Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**

What is the **probability** of this point to be **blue**?
Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**

What is the **probability** of this point to be **blue**?
Where these probabilities or scores come from?

Probability for the point to belong to positive class

What is the probability of this point to be blue?
Almost every **model** can output **probability** for each point to belong to a **certain class**.

Where these **probabilities** or **scores** come from?

**Probability** for the point to belong to **positive class**

What is the **probability** of this point to be **blue**?
Can we please have just one number?

Let's assume that we have a classifier that assigned the following probabilities of a data point to be positive (i.e. blue)
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9  0.8  0.7  0.6  0.5

Let's assume that we have a classifier that assigned the following probabilities of a data point to be positive (i.e. blue)
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9 0.8 0.7 0.6 0.5
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>●</td>
</tr>
</tbody>
</table>

Above what probability we will consider point to be predicted as positive?
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

0.9  0.8  0.7  0.6  0.5

Above what probability we will consider point to be predicted as **positive**?

We shall consider **all possible** threshold values!
Can we please have just one number?

Classifier scores (probabilities) of bing **positive**:

0.9  0.8  0.7  0.6  0.5

If probability is $\geq 1.0$ the data point is predicted **positive**
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

If probability is $\geq 1.0$ the data point is predicted positive.
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

\[ \geq 1.0 \]

<table>
<thead>
<tr>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>✍️</td>
<td>📊</td>
<td>✍️</td>
<td>✍️</td>
<td>📊</td>
</tr>
</tbody>
</table>
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th>Threshold</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td>■</td>
<td>◼️</td>
<td>◼️</td>
<td>◼️</td>
<td>◼️</td>
</tr>
</tbody>
</table>

What are the values in the confusion matrix for such **threshold**?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 1.0</td>
<td><img src="0.9" alt="Predicted" /></td>
<td><img src="TN" alt="Actual" /></td>
</tr>
<tr>
<td></td>
<td><img src="0.8" alt="Predicted" /></td>
<td><img src="FP" alt="Actual" /></td>
</tr>
<tr>
<td></td>
<td><img src="0.7" alt="Predicted" /></td>
<td><img src="FN" alt="Actual" /></td>
</tr>
<tr>
<td></td>
<td><img src="0.6" alt="Predicted" /></td>
<td><img src="TP" alt="Actual" /></td>
</tr>
<tr>
<td></td>
<td><img src="0.5" alt="Predicted" /></td>
<td></td>
</tr>
</tbody>
</table>

What are the values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Classifier Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 1.0</td>
</tr>
<tr>
<td>0.9</td>
</tr>
<tr>
<td>0.8</td>
</tr>
<tr>
<td>0.7</td>
</tr>
<tr>
<td>0.6</td>
</tr>
<tr>
<td>0.5</td>
</tr>
</tbody>
</table>

What are the values in the confusion matrix for such threshold?

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td></td>
<td>FP</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>TP</td>
</tr>
<tr>
<td>FN</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

What are the values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- Actual:
  - $\geq 1.0$: 0
  - $0.9$: 0
  - $0.8$: 0
  - $0.7$: 1
  - $0.6$: 0
  - $0.5$: 0

- Predicted:
  - $\geq 1.0$: 2
  - $0.9$: 1
  - $0.8$: 1
  - $0.7$: 2
  - $0.6$: 1
  - $0.5$: 1

What are the values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

What are the values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Threshold</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FN</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

What are the values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9  0.8  0.7  0.6  0.5

Predicted

<table>
<thead>
<tr>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>
Can we please have just one number?

This threshold is associated with one point on this graph.

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FN</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TP</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Score</th>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>✉️</td>
<td>⚫</td>
</tr>
<tr>
<td>0.8</td>
<td>✉️</td>
<td>⚫</td>
</tr>
<tr>
<td>0.7</td>
<td>✉️</td>
<td>⚫</td>
</tr>
<tr>
<td>0.6</td>
<td>✉️</td>
<td>⚫</td>
</tr>
<tr>
<td>0.5</td>
<td>✉️</td>
<td>⚫</td>
</tr>
</tbody>
</table>

Where is this point?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

Where is this point?

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>2</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
<tr>
<td>FN</td>
<td>3</td>
</tr>
<tr>
<td>TP</td>
<td>0</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Score</th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

Where is this point?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>■</td>
<td>○</td>
<td>■</td>
<td>■</td>
<td>■</td>
</tr>
</tbody>
</table>

Where is this point?

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>3</td>
</tr>
<tr>
<td>TP</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>2</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Threshold of $\geq 1.0$ is associated with point $(0,0)$ on this graph.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>FP</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>FN</td>
<td>TP</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9  0.8  0.7  0.6  0.5
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9  0.8  0.7  0.6  0.5

Time to choose another threshold. What it could be?
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

If probability is $\geq 0.9$ the data point is predicted **positive**
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Probability</th>
<th>False Positive Rate</th>
<th>True Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>&gt;= 0.9</td>
<td>&gt;= 1.0</td>
</tr>
<tr>
<td>0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

False Positive Rate: \( \frac{FP}{FP + TN} \)

True Positive Rate: \( \frac{TP}{TP + FN} \)
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

>= 0.9

<table>
<thead>
<tr>
<th>Score</th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

$\geq 0.9$

Predicted

Actual

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="positive.png" alt="Positive" /></td>
<td><img src="positive.png" alt="Positive" /></td>
<td><img src="positive.png" alt="Positive" /></td>
<td><img src="positive.png" alt="Positive" /></td>
<td><img src="positive.png" alt="Positive" /></td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Classifier Score</th>
<th>True Positive Rate (TP/(TP + FN))</th>
<th>False Positive Rate (FP/(FP + TN))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>1</td>
<td>&gt;= 0.9</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>&gt;= 0.9</td>
</tr>
<tr>
<td>0.7</td>
<td>1</td>
<td>&gt;= 0.9</td>
</tr>
<tr>
<td>0.6</td>
<td>1</td>
<td>&gt;= 0.9</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>&gt;= 0.9</td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Probability</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td><img src="" alt="Predicted Values" /></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

What are the new values in the confusion matrix for such threshold? 

Classifier scores (probabilities) of bing positive: 

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Classifier Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.9</td>
<td>0.9 0.8 0.7 0.6 0.5</td>
</tr>
</tbody>
</table>

Predicted

Actual

FP

TP
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th>Score</th>
<th>TP Rate</th>
<th>FP Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0.8</td>
<td>0.7</td>
</tr>
<tr>
<td>0.6</td>
<td>0.5</td>
<td></td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such **threshold**?

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>FP</td>
<td>2</td>
</tr>
<tr>
<td>TP</td>
<td>2</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Probability</th>
<th>True Positive Rate</th>
<th>False Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0.7</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0.6</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0.5</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

What are the new values in the confusion matrix for such threshold?

Predicted | Actual |
---|---|
○ | 2 |
○ | 0 |
△ | 2 |
TP |

False Positive Rate
FP/(FP + TN)

True Positive Rate
TP/(TP + FN)
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

>= 0.9

What are the new values in the confusion matrix for such threshold?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

What are the new values in the confusion matrix for such threshold?

Predicted

Actual
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

>= 0.9

0.9 0.8 0.7 0.6 0.5

What are the new values in the confusion matrix for such threshold?

Actual

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

True Positive Rate

\[
\text{TP}/(\text{TP} + \text{FN})
\]

False Positive Rate

\[
\text{FP}/(\text{FP} + \text{TN})
\]
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

Predicted:

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>2</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
<tr>
<td>FN</td>
<td>2</td>
</tr>
<tr>
<td>TP</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.9</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
<td>[ ]</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
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<td>2</td>
<td></td>
</tr>
<tr>
<td>TP</td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

Predicted

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TN</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
</tbody>
</table>

Where is this point?
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th>Score</th>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Where is this **point**?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Classifier Score</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>0.8</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

False Positive Rate

True Positive Rate

>= 0.9 threshold is associated with point (0, 1/3) on this graph.

Predicted

Actual
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.8</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.7</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.6</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

Diagram:

- True Positive Rate: $\frac{TP}{TP + FN}$
- False Positive Rate: $\frac{FP}{FP + TN}$

- Points marked for classifier scores $\geq 1.0$ are shown as red circles.
- Points marked for classifier scores $\geq 0.9$ are shown as blue squares.
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

If probability is \( \geq 0.8 \) the data point is predicted positive.

### True Positive Rate
\[
\text{TP/(TP + FN)}
\]

### False Positive Rate
\[
\text{FP/(FP + TN)}
\]
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Probability</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>0.7</td>
<td>0.6</td>
</tr>
<tr>
<td>0.5</td>
<td></td>
</tr>
</tbody>
</table>

Actual vs. Predicted:

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>TP</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

<table>
<thead>
<tr>
<th>Probability</th>
<th>True Positive Rate</th>
<th>False Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>1/(1 + 2)</td>
<td>1/(1 + 1)</td>
</tr>
<tr>
<td>0.8</td>
<td>1/(1 + 2)</td>
<td>1/(1 + 1)</td>
</tr>
<tr>
<td>0.7</td>
<td>1/(1 + 2)</td>
<td>1/(1 + 1)</td>
</tr>
<tr>
<td>0.6</td>
<td>1/(1 + 2)</td>
<td>1/(1 + 1)</td>
</tr>
<tr>
<td>0.5</td>
<td>1/(1 + 2)</td>
<td>1/(1 + 1)</td>
</tr>
</tbody>
</table>

Actual  Predicted

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Score</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>□</td>
</tr>
<tr>
<td>0.8</td>
<td>□</td>
</tr>
<tr>
<td>0.7</td>
<td>□</td>
</tr>
<tr>
<td>0.6</td>
<td>□</td>
</tr>
<tr>
<td>0.5</td>
<td>□</td>
</tr>
</tbody>
</table>

Actual
- TN
- FP
- FN
- TP

Predicted
- □
- ○

True Positive Rate
- 1/3
- >= 0.9
- 1/2
- >= 1.0

False Positive Rate
- 1/2
- >= 1.0
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

>= 0.8

<table>
<thead>
<tr>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>[■]</td>
<td>[○]</td>
<td>[■]</td>
<td>[■]</td>
<td>[○]</td>
</tr>
</tbody>
</table>

>= 0.8 threshold is associated with point (1/2, 1/3) on this graph.

Actual

<table>
<thead>
<tr>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

Predicted

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9  0.8  0.7  0.6  0.5

- True Positive Rate: $\frac{TP}{TP + FN}$
- False Positive Rate: $\frac{FP}{FP + TN}$

Note: At least 0.8
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

- $0.9$
- $0.8$
- $0.7$
- $0.6$
- $0.5$

$\text{Actual}$

<table>
<thead>
<tr>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

$\text{Predicted}$

<table>
<thead>
<tr>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>
Can we please have just one number?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Score</th>
<th>True Positive Rate</th>
<th>False Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 0.7</td>
<td>0.9</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

- True Positive Rate
- False Positive Rate
- TN: True Negative
- FP: False Positive
- FN: False Negative
- TP: True Positive
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

- $0.9$
- $0.8$
- $0.7$
- $0.6$
- $0.5$

<table>
<thead>
<tr>
<th>True Positive Rate $\frac{TP}{(TP + FN)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;= 1.0</td>
</tr>
<tr>
<td>&gt;= 0.9</td>
</tr>
<tr>
<td>&gt;= 0.8</td>
</tr>
<tr>
<td>&gt;= 0.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>False Positive Rate $\frac{FP}{(FP + TN)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TP</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><img src="image" alt="Red Circles" /></td>
<td><img src="image" alt="Blue Circles" /></td>
<td><img src="image" alt="Blue Circles" /></td>
<td><img src="image" alt="Blue Rectangles" /></td>
<td><img src="image" alt="Red Circles" /></td>
</tr>
</tbody>
</table>

True Positive Rate

\[ \frac{TP}{TP + FN} \]

False Positive Rate

\[ \frac{FP}{FP + TN} \]
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Classifier Score</th>
<th>0.9</th>
<th>0.8</th>
<th>0.7</th>
<th>0.6</th>
<th>0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td>![Predicted Symbols]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th>Actual</th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Actual</th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- >= 0.9: 0.9
- >= 0.8: 0.8
- >= 0.7: 0.7
- >= 0.6: 0.6
- >= 0.5: 0.5

Actual vs Predicted:

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Positive Rate: 1</td>
<td></td>
</tr>
<tr>
<td>False Positive Rate: 1/2</td>
<td></td>
</tr>
<tr>
<td>True Negative: 0</td>
<td></td>
</tr>
<tr>
<td>False Positive: 1</td>
<td></td>
</tr>
<tr>
<td>True Positive: 3</td>
<td></td>
</tr>
</tbody>
</table>

Diagram showing the ROC curve with points at:
- >= 0.9: 0.9
- >= 0.8: 0.8
- >= 0.7: 0.7
- >= 0.6: 0.6
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Score</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>0.8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>0.7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>0.6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>0.5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

False Positive Rate: 1/2

True Positive Rate

Actual

Predicted

>= 0.6

>= 0.7

>= 0.8

>= 0.9

Can we please have just one number?
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- True Positive Rate: $\frac{TP}{TP + FN}$
- False Positive Rate: $\frac{FP}{FP + TN}$

<table>
<thead>
<tr>
<th>Probability</th>
<th>&gt;= 0.9</th>
<th>&gt;= 0.8</th>
<th>&gt;= 0.7</th>
<th>&gt;= 0.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color</td>
<td>⬤</td>
<td>⬤</td>
<td>⬤</td>
<td></td>
</tr>
</tbody>
</table>

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

$\geq 1.0$

$\geq 0.9$

$\geq 0.8$

$\geq 0.7$

$\geq 0.6$

True Positive Rate $\frac{TP}{TP + FN}$

False Positive Rate $\frac{FP}{FP + TN}$
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

<table>
<thead>
<tr>
<th>Classifier Score</th>
<th>True Positive Rate</th>
<th>False Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>0.8</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>0.7</td>
<td>0.7</td>
<td>0.3</td>
</tr>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>
Can we please have just **one** number?

Classifier scores (probabilities) of bing **positive**:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

<table>
<thead>
<tr>
<th>True Positive Rate</th>
<th>False Positive Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{3}{3 + 0}$</td>
<td>$\frac{2}{2 + 0}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>TN</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>2</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TP</td>
<td>3</td>
</tr>
</tbody>
</table>
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

0.9 0.8 0.7 0.6 0.5

TP

FP

TN

FN

0 2

0 3
Can we please have just one number?

Classifier scores (probabilities) of bing positive:

- 0.9
- 0.8
- 0.7
- 0.6
- 0.5

Actual
- TP
- FN

Predicted
- TN
- FP

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>TP</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>
Can we please have just **one** number?

Let's connect these points with a **line**
Can we please have just one number?

Let's connect these points with a line.
Can we please have just one number?

Let's connect these points with a line.
Can we please have just one number?

Let's connect these points with a line.
Can we please have just one number?

Let's connect these points with a line.
Can we please have just one number?

Let's connect these points with a line.
Can we please have just **one** number?

This line is called **Receiver Operating Characteristic**

**True Positive Rate**
\[
\frac{TP}{TP + FN}\]

**False Positive Rate**
\[
\frac{FP}{FP + TN}\]
Can we please have just **one** number?

This line is called **Receiver Operating Characteristic**

\[
\text{True Positive Rate} = \frac{TP}{TP + FN} \\
\text{False Positive Rate} = \frac{FP}{FP + TN}
\]
Can we please have just one number?

This line is called ROC curve.
Can we please have just one number?

True Positive Rate

\[ \frac{TP}{TP + FN} \]

False Positive Rate

\[ \frac{FP}{FP + TN} \]

This line is called ROC curve.
Can we please have just one number?

This line is called ROC curve.
Can we please have just one number?

This line is called ROC curve

Different thresholds

- TP/(TP + FN)
- FP/(FP + TN)
ROC itself is not meaningful, the area under this curve is what we are after.

\[
\text{True Positive Rate} \quad \frac{TP}{TP + FN} \quad \text{False Positive Rate} \quad \frac{FP}{FP + TN}
\]

This line is called ROC curve.
ROC itself is not meaningful, the area under this curve is what we are after.

This line is called ROC curve.
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).
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We are interested in the area of this polygon.
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

In the meantime we know that the area of this square is

\[ 1 \times 1 = 1 \]
In the meantime we know that the area of this square is \(1 \times 1 = 1\).
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

We are interested in the area of this polygon.

How to find this area?

True Positive Rate $\frac{TP}{TP + FN}$

False Positive Rate $\frac{FP}{FP + TN}$
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

We are interested in the area of this polygon.

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True Positive Rate $\frac{TP}{TP + FN}$

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ROC itself is not meaningful, the area under this curve is what we are after.

Let’s compute the area under the curve (AUC).

How to find this area?

We are interested in the area of this polygon.
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

We are interested in the area of this polygon:

\[
\frac{1}{2} \times \frac{2}{3}
\]

\[
= \frac{2}{6}
\]

\[
= \frac{1}{3}
\]
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

We are interested in the area of this polygon.
In the meantime we know that the area of this square is $1 \times 1 = 1$.
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In the meantime we know that the area of this square is $1 \times 1 = 1$.
ROC itself is not meaningful, the area under this curve is what we are after.

Let's compute the area under the curve (AUC).

Area is 0.66
ROC itself is not meaningful, the area under this curve is what we are after.

**AUC** is a measure from 0 to 1.

TP/(TP + FN)

FP/(FP + TN)
ROC itself is not meaningful, the area under this curve is what we are after.

Area of 1.0 is a perfect classifier.

AUC is a measure from 0 to 1.
ROC itself is not meaningful, the area under this curve is what we are after.

AUC is a measure from 0 to 1.

True Positive Rate
\[
\frac{TP}{TP + FN}
\]

False Positive Rate
\[
\frac{FP}{FP + TN}
\]

Area of 0.5 is a random classifier.
**True Positive Rate**

\[
\text{TP/(TP + FN)}
\]

**False Positive Rate**

\[
\text{FP/(FP + TN)}
\]

Area of 0.5 is a **random classifier**

Area is **0.66**
So our **classifier** is better than **random**

(AUC 0.66 > AUC 0.5)
So our **classifier** is better than **random** (AUC 0.66 > AUC 0.5)

Hey! Did not you say that **being better than random** is not enough? Would **AUC** help to detect **majority** class prediction?
Coming back to unbalanced example
Coming back to unbalanced example

What do you think are classifier scores in this case?
Coming back to unbalanced example

What do you think are classifier **scores** in this case?

Scores are *the same* and usually very **high** (1.0) for each point.
What do you think are classifier **scores** in this case?

![ROC Curve with scores](image)
What do you think are classifier scores in this case?

If score is $\geq 1.0$ the data point is predicted positive.
What do you think are classifier scores in this case?

If score is $\geq 1.0$ the data point is predicted positive.

Predicted

Actual

True Positive Rate

$\frac{TP}{TP + FN}$

False Positive Rate

$\frac{FP}{FP + TN}$

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>?</td>
</tr>
<tr>
<td></td>
<td>TN</td>
</tr>
<tr>
<td></td>
<td>FP</td>
</tr>
<tr>
<td></td>
<td>TP</td>
</tr>
</tbody>
</table>

[1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0]
What do you think are classifier scores in this case?

If score is $\geq 1.0$ the data point is predicted **positive**

---

**True Positive Rate**

$$\frac{TP}{TP + FN}$$

**False Positive Rate**

$$\frac{FP}{FP + TN}$$

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
</tr>
<tr>
<td>TP</td>
<td>9</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
</tr>
</tbody>
</table>
What do you think are classifier scores in this case?

If score is $\geq 1.0$ the data point is predicted positive.

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>TP</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Predicted

<p>| | |</p>
<table>
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<td></td>
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</tbody>
</table>

True Positive Rate

$\frac{9}{9+0}$

False Positive Rate

$\frac{1}{1+0}$
What do you think are classifier scores in this case?

If score is $\geq 1.0$ the data point is predicted positive.
What do you think are classifier scores in this case?

What other thresholding option we can use?
What do you think are classifier scores in this case?

If score is > 1.0 the data point is predicted positive.
What do you think are classifier scores in this case?

If score is $>1.0$ the data point is predicted positive.
What do you think are classifier scores in this case?

If score is $> 1.0$ the data point is predicted positive.

Actual

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>?</td>
<td>TP</td>
</tr>
</tbody>
</table>

Predicted

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>?</td>
<td>TP</td>
</tr>
</tbody>
</table>

True Positive Rate

$\frac{TP}{TP + FN}$

False Positive Rate

$\frac{FP}{FP + TN}$
What do you think are classifier scores in this case?

If score is > 1.0 the data point is predicted positive.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

True Positive Rate: \( \frac{TP}{TP + FN} \)

False Positive Rate: \( \frac{FP}{FP + TN} \)
What do you think are classifier scores in this case?

If score is \( > 1.0 \) the data point is predicted **positive**

**Actual**

<table>
<thead>
<tr>
<th></th>
<th>TN</th>
<th>FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

**Predicted**

<table>
<thead>
<tr>
<th></th>
<th>TP</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>FN</td>
<td>9</td>
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</tbody>
</table>
What do you think are classifier **scores** in this case?

If score is > 1.0 the data point is predicted **positive**

<table>
<thead>
<tr>
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<th>Predicted</th>
</tr>
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<tr>
<td>FN</td>
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<tr>
<td>TN</td>
<td>1</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
</tr>
</tbody>
</table>
True Positive Rate
\[
\frac{TP}{TP + FN}
\]

False Positive Rate
\[
\frac{FP}{FP + TN}
\]
True Positive Rate
\[ \frac{TP}{TP + FN} \]

False Positive Rate
\[ \frac{FP}{FP + TN} \]

\[ \geq 1.0 \]
True Positive Rate

$\frac{TP}{TP + FN}$

False Positive Rate

$\frac{FP}{FP + TN}$

$\geq 1.0$

ROC
True Positive Rate: $\frac{TP}{TP + FN}$

False Positive Rate: $\frac{FP}{FP + TN}$

ROC: Receiver Operating Characteristic

$\geq 1.0$
True Positive Rate
\[
\frac{TP}{TP + FN}
\]

False Positive Rate
\[
\frac{FP}{FP + TN}
\]

AUC is 0.5

ROC

>= 1.0
If AUC is close to 0.5 the classifier should not be trusted.

FP/(FP + TN)  

ROC

AUC is 0.5

>= 1.0

True Positive Rate  

TP/(TP + FN)
If AUC is close to **0.5** the classifier should not be trusted

Our classifier:

\[
\text{TP} \quad / \quad (\text{TP} + \text{FN})
\]

\[
\text{FP} \quad / \quad (\text{FP} + \text{TN})
\]

AUC is 0.5

Area is 0.66
So far...

Accuracy = 80%

Confusion matrix

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Predicted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recall</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Precision</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>F1-score/Dice</td>
<td>6/7</td>
<td></td>
</tr>
</tbody>
</table>
So far…

Classifier \( X \)

AUC is 0.66
So far...

Area of 1.0 is a perfect classifier

$$\text{Area of 1.0 is a perfect classifier}$$
So far...

Area of **1.0** is a **perfect** classifier

If AUC is close to **0.5** the classifier should not be trusted

AUC is **1**

AUC is **0.5**
So far…

**ROC (AUC)** is not necessarily instead of other metrics (accuracy, recall, confusion matrix etc). It can be used **in addition**
That's all Folks!

BIIT

www.slideshare.net/DimaFishman